

Bridging or Widening the Gap? Exploring the Determinants of AI Tool Adoption and Its Differential Impacts on Chinese Learning Outcomes among International Students in China

Xiaoli Hu, Mengzhen Jia, Xueyuan Wu

Jiangsu Maritime Institute, Nanjing 211170, Jiangsu, China

Abstract: *The rapid integration of artificial intelligence (AI) tools into language learning practices has raised critical questions about educational equity, particularly among culturally and linguistically diverse student populations. This study investigates the usage patterns, determinants, and differential impacts of AI tools—including machine translation, intelligent writing assistants, speech recognition, and conversational chatbots—among international students learning Chinese in Jiangsu’s higher vocational institutions. Drawing on survey data from 256 respondents and follow-up qualitative interviews with 18 purposefully selected participants, the study examines how factors such as Chinese proficiency (HSK level), prior technology experience, academic motivation, and cultural background influence both the frequency and the effectiveness of AI tool use. Results indicate significant intra-group variation: while most students use AI tools primarily for vocabulary acquisition and homework completion, a notable subset relies heavily on AI for tasks requiring higher-order thinking, leading to a performance paradox—short-term gains in task completion versus long-term skill erosion. Using hierarchical regression analysis and thematic coding, the study identifies digital literacy ($\beta = 0.215, p < 0.001$) and teacher guidance ($\beta = 0.248, p < 0.001$) as the most critical buffers against the negative effects of AI over-reliance. Chinese proficiency emerged as the strongest protective factor against divide effects ($\beta = -0.218, p < 0.001$). The findings contribute to the theoretical extension of the Digital Divide framework in the context of AI-enhanced language education and offer practical strategies for designing AI-literacy training and usage guidelines tailored to international students in vocational college settings.*

Keywords: AI tools; Digital divide, Chinese learning, International students, Higher vocational colleges, Technology adoption, Educational inequality, Academic integrity, Mixed methods.

1. Introduction

1.1 The AI Revolution in Language Education

The proliferation of generative artificial intelligence has fundamentally transformed the landscape of language education. Tools such as ChatGPT, Deepseek, Google Translate, and Duolingo have transitioned from emerging technologies to everyday utilities, with the global AI education market projected to reach \$80 billion by 2030. Language learning represents one of the most prominent application domains, as AI technologies excel at providing instant translation, automated writing feedback, conversational practice, and personalized content generation.

For international students learning Chinese as a second language, AI tools are particularly consequential. Chinese, classified as a Category IV language by the Foreign Service Institute, requires approximately 2,200 hours of study for native English speakers to achieve proficiency—substantially more than European languages. The cognitive and emotional demands of this learning journey are compounded by the challenges of living in a culturally unfamiliar environment, navigating complex social interactions, and meeting academic requirements in a foreign language.

1.2 The Promise and Peril of AI in Education

Scholars have extensively documented the empowering potential of AI in educational contexts. Adaptive learning systems can tailor content to individual proficiency levels (Chen et al., 2023), intelligent tutoring systems provide

immediate, corrective feedback (Wang et al., 2024), and conversational agents offer low-anxiety practice opportunities. For language learners specifically, AI tools lower the threshold for comprehension, enabling access to authentic materials that would otherwise be inaccessible, and provide scaffolded support for production tasks.

However, a growing body of critical scholarship has raised concerns about the unintended consequences of AI integration in education. These include cognitive offloading—the tendency to rely on AI for tasks that would otherwise develop cognitive skills—reduction in critical thinking engagement (Bailin, 2024), homogenization of creative output, and risks to academic integrity (Cotton et al., 2024). For language learners, over-reliance on AI translation and generation tools may impede the development of communicative competence, as students outsource rather than cultivate linguistic skills.

1.3 The Digital Divide Revisited

The concept of the digital divide has evolved considerably since its initial formulation. Early research focused on the “access gap”—the binary distinction between those with and without physical access to digital technologies (Norris, 2001). Van Dijk’s (2005, 2024) more sophisticated framework conceptualizes digital inequality as operating through four sequential barriers: motivational access, physical access, skills access, and usage access. More recently, scholarship has identified a “second-level” divide concerning differences in how individuals use technology, and a “third-level” divide concerning differences in the outcomes and benefits derived from technology use.

In the context of AI-enhanced education, these layers manifest in new forms. Students may have equivalent physical access to AI tools yet differ dramatically in their capacity to deploy them effectively—distinguishing between those who use AI for surface-level task completion versus those who leverage it for deeper learning and critical engagement. This “cognitive divide” represents a particularly insidious form of inequality, as it may be less visible but no less consequential than traditional access disparities.

1.4 International Students in Chinese Vocational Colleges: A Unique Population

International students in China’s higher vocational colleges represent a distinct and under-researched population. Unlike their counterparts in research-oriented universities, vocational students typically enroll in shorter programs (2-3 years), pursue more applied curricula, and often enter with lower Chinese proficiency. Many are sponsored by Belt and Road Initiative scholarships, hailing from countries with varying educational infrastructures and digital resources. Approximately 5% of China’s international student population—over 25,000 students—study in vocational institutions, and this number continues to grow (Ministry of Education, 2025).

This population faces unique vulnerabilities. The compressed timeline of vocational programs leaves less room for gradual language acquisition. The practical, industry-embedded nature of their training demands immediate functional competence in Chinese. Furthermore, many vocational college international students come from lower-resourced educational backgrounds, potentially with less prior experience in digital learning environments. For this group, AI tools represent both a lifeline and a potential trap—a means of overcoming immediate linguistic barriers that may simultaneously undermine long-term skill development.

1.5 Research Gaps

Despite the accelerating integration of AI into language education and the growing presence of international students in Chinese vocational colleges, several significant gaps persist in the literature.

First, research on AI-assisted language learning predominantly focuses on English as a Second Language (ESL) contexts or on Chinese learning among university students. The vocational college international student population remains largely invisible in this scholarship, despite their distinct learning needs, constraints, and trajectories.

Second, existing research overwhelmingly adopts a technology-optimistic stance, emphasizing the empowering potential of AI while neglecting to systematically examine its risks, particularly the potential to create or exacerbate digital divides. Critical, balanced examinations of AI’s dual effects are rare.

Third, most studies employ purely quantitative or purely qualitative designs, limiting their capacity to capture both the prevalence and the lived experience of AI-related phenomena.

The field lacks integrated, mixed-methods investigations that can establish patterns while illuminating underlying mechanisms.

Fourth, the role of moderating factors—particularly institutional support structures, teacher guidance, and pedagogical design—in shaping the relationship between AI use and learning outcomes remains undertheorized and underinvestigated.

1.6 Research Questions

This study addresses these gaps through the following research questions:

What are the patterns of AI tool usage (types, frequency, scenarios, purposes) among international students in Jiangsu vocational colleges for Chinese language learning?

What individual, environmental, and technological factors significantly predict both the frequency and the effectiveness of AI tool use?

What differential impacts do AI tools have on students with varying Chinese proficiency, digital literacy, and academic motivation?

What support needs do students articulate regarding AI tool usage, and how do these align with existing institutional provisions?

2. Literature Review

2.1 AI Tools in Language Learning: A Typology

AI tools relevant to Chinese language learning can be categorized into several functional types. **Translation and interpretation tools**, such as Google Translate, DeepL, and Baidu Translate, provide immediate lexical and sentential translation. **Intelligent writing assistants**, such as Grammarly and Deepseek’s writing functions, offer automated grammar correction and stylistic suggestions. **Conversational agents and chatbots**, including ChatGPT, Duolingo Max, and specialized Chinese chatbots, enable interactive, simulated conversation practice. **Speech recognition and pronunciation tools** support speaking skill development through automated phonetic analysis. **Personalized learning platforms** adapt content sequencing and practice frequency to individual learner profiles.

Research indicates that international students in China use these tools extensively, with usage rates exceeding 85% in some studies (Wang & Sun, 2024). However, the quality and nature of this usage vary considerably, from strategic, metacognitive engagement to passive, task-completion orientation.

2.2 Determinants of Technology Adoption in Language Learning

The Technology Acceptance Model (TAM), proposed by Davis (1989), provides a foundational framework for understanding technology adoption. According to TAM, two

primary factors determine technology acceptance: **perceived usefulness** (the degree to which a user believes that using a particular technology would enhance their performance) and **perceived ease of use** (the degree to which a user believes that using a particular technology would be free of effort). Subsequent research has extended TAM to include additional factors such as social influence, self-efficacy, and facilitating conditions (Venkatesh et al., 2003).

In the context of language learning, research has identified several additional determinants of AI tool adoption. **Language proficiency** significantly influences technology use patterns, with lower-proficiency learners more likely to use AI for basic comprehension and higher-proficiency learners more likely to use it for refinement and advanced tasks (Li et al., 2021). **Prior technology experience** shapes both the willingness to adopt new tools and the capacity to use them effectively. **Academic motivation** influences whether students use AI strategically for learning or instrumentally for task completion (Zhou et al., 2022). Cultural factors, including attitudes toward technology and preferences for help-seeking, also shape adoption patterns (Xiao, 2021).

2.3 Differential Impacts of AI on Learning Outcomes

The impacts of AI tool use on learning outcomes are not uniform across learners. Several studies have documented differential effects based on learner characteristics.

By proficiency level: Research consistently demonstrates that lower-proficiency learners are more vulnerable to the negative effects of AI over-reliance. Students with lower English proficiency who used AI writing assistants showed less improvement in writing accuracy over time compared to higher-proficiency users, suggesting that AI use may accelerate rather than close proficiency gaps.

By digital literacy: Students with higher digital literacy—the capacity to critically evaluate and effectively use digital technologies—derive greater benefit from AI tools and experience fewer negative consequences (Ng et al., 2021).

By academic motivation: Students with intrinsic motivation—learning for the sake of learning—tend to use AI as a tool for deeper understanding, while extrinsically motivated students use it primarily for task completion (Gagné & Deci, 2005; Zhou et al., 2022). This motivational difference shapes whether AI use enhances or undermines long-term learning.

2.4 The Performance Paradox in AI-Assisted Learning

A growing body of research has identified what may be termed the “performance paradox” in AI-assisted learning: while AI tools reliably improve immediate performance on tasks (higher grades, faster completion), they may simultaneously undermine long-term skill development and transferable competence.

Risko and Gilbert (2024) demonstrated in their meta-analysis that reliance on digital cognitive aids significantly impairs subsequent recall and problem-solving, particularly for information that learners anticipate being able to access later. This “cognitive offloading” effect may be particularly

pronounced in language learning, where the goal is not just task completion but the internalization of linguistic knowledge.

Cotton and colleagues (2024) found that students who regularly used generative AI for writing assignments showed less improvement in independent writing tasks over the course of a semester compared to students who used AI minimally or not at all. This suggests that the immediate benefits of AI use may come at the cost of slower skill development.

2.5 Institutional Responses and the Role of Teacher Guidance

Educational institutions worldwide have responded to AI integration in varied ways. At one extreme, outright prohibition of AI use in academic settings has been adopted by some educational systems, driven by concerns about academic integrity and skill development. At the other extreme, laissez-faire approaches leave AI use largely unregulated, assuming that technology integration is inevitable and that students will adapt appropriately.

A growing consensus favors a middle ground: teaching AI literacy alongside content instruction (Ng et al., 2021). This approach involves developing students’ capacity to understand what AI can and cannot do, evaluate AI output critically, use AI as a tool rather than a replacement for cognition, and maintain academic integrity in AI-involved work.

Teacher guidance plays a particularly critical role. Wang and Sun (2024) found that teacher modeling of AI use and explicit discussion of AI-related academic integrity issues significantly improved students’ ability to use AI effectively and ethically. Students who received clear guidance reported more balanced usage patterns and greater learning benefits.

2.6 The Present Study

This study contributes to the literature by providing the first systematic, mixed-methods investigation of the determinants and differential impacts of AI tool usage in Chinese language learning among international students in Chinese vocational colleges. By integrating quantitative survey data with qualitative interview data, the study captures both the prevalence and the lived experience of AI-related phenomena. By examining moderating factors including Chinese proficiency, digital literacy, and teacher guidance, the study identifies the conditions under which AI use empowers versus divides.

3. Methods

3.1 Research Design

This study employed a sequential explanatory mixed-methods design (Creswell & Plano Clark, 2018), consisting of two integrated phases. The quantitative phase involved cross-sectional survey data collection to establish usage patterns, identify predictors, and test moderating relationships. The subsequent qualitative phase used semi-structured interviews to explain and elaborate on quantitative findings,

capturing the subjective experiences and contextual factors behind statistical patterns.

3.2 Participants

3.2.1 Quantitative Phase

A stratified random sampling strategy was employed across three vocational colleges in Jiangsu Province: Jiangsu Maritime Institute (JMI), Nanjing Polytechnic Institute (NPI), and Yangzhou Polytechnic Institute (YPI). These institutions represent diverse vocational education contexts, encompassing maritime, engineering, and comprehensive programs.

Inclusion criteria for participation were: (a) current enrollment as an international student; (b) enrollment in a diploma-granting program of at least two years' duration; (c) active engagement in Chinese language learning; and (d) willingness to provide informed consent.

Exclusion criteria were: (a) exchange students on programs shorter than one semester; (b) students who had been in China for less than one month; and (c) students unable to complete the survey in either Chinese or English.

Three hundred twenty surveys were distributed. After excluding 64 responses with patterned answering, missing data exceeding 20%, or incomplete demographic information, 256 valid responses were retained (valid response rate: 80.0%). Participants' age ranged from 18 to 34 ($M = 22.7$, $SD = 3.3$). Detailed demographic characteristics are presented in Table 1.

Table 1: Demographic Characteristics of Quantitative Participants (N = 256)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	167	65.2
	Female	89	34.8
Institution	JMI	94	36.7
	NPI	87	34.0
	YPI	75	29.3
Year of Study	Year 1	117	45.7
	Year 2	102	39.8
	Year 3	37	14.5
HSK Level	Below Level 3	52	20.3
	Level 3	82	32.0
	Level 4	75	29.3
	Level 5 or above	47	18.4
Region of Origin	Southeast Asia	94	36.7
	South Asia	56	21.9
	Central Asia	46	18.0
	Africa	39	15.2
	Other	21	8.2
Age Group	18–20	68	26.6
	21–23	112	43.8
	24–26	51	19.9
	27+	25	9.8

3.2.2 Qualitative Phase

Eighteen participants were purposefully sampled from survey respondents based on their composite AI usage patterns, Chinese proficiency level, and reported learning outcomes. Sampling strategy ensured representation across: (a) HSK

levels (Level 3 and below; Level 4; Level 5 and above); (b) AI usage frequency (high, moderate, low); (c) reported empowerment-divide balance (empowerment-dominant, balanced, divide-dominant); (d) gender; and (e) region of origin.

Participants provided written informed consent for audio-recorded interviews. All names used in reporting are pseudonyms.

3.3 Instruments

3.3.1 Quantitative Instruments

Demographics and Background. Items captured gender, age, institution, year of study, major, HSK level, length of stay in China, region of origin, prior technology experience, and internet access stability.

AI Tool Usage Patterns. Participants were presented with a comprehensive inventory of AI tools organized by functional category: translation tools, conversational AI, intelligent writing assistants, speech recognition/pronunciation tools, personalized learning platforms, and other. For each tool, participants indicated: (1) ever used (yes/no); (2) frequency of use (1 = Never, 5 = Daily); (3) primary purpose (multiple selection); and (4) perceived usefulness (1 = Not useful at all, 5 = Extremely useful).

Empowerment Effects Scale. A 20-item scale assessed perceived empowerment from AI tool usage, covering four dimensions: learning efficiency enhancement ($\alpha = 0.87$); personalized learning support ($\alpha = 0.84$); reduced learning barriers ($\alpha = 0.82$); and increased motivation and confidence ($\alpha = 0.85$). The full scale demonstrated excellent reliability (Cronbach's $\alpha = 0.92$).

Digital Divide Effects Scale. A 24-item scale assessed potential negative consequences, covering four dimensions: technological dependency ($\alpha = 0.86$); critical thinking erosion ($\alpha = 0.83$); academic integrity concerns ($\alpha = 0.79$); and learning outcome compromise ($\alpha = 0.81$). The full scale demonstrated good reliability (Cronbach's $\alpha = 0.89$).

AI Literacy Scale. A 12-item scale assessed capacity to understand, evaluate, and use AI tools effectively. The scale demonstrated acceptable reliability (Cronbach's $\alpha = 0.84$).

Teacher Guidance Regarding AI Scale. A 6-item scale assessed perceptions of teacher support and guidance regarding AI tool use, demonstrating good reliability (Cronbach's $\alpha = 0.87$).

Chinese Language Proficiency. Self-assessed proficiency was measured using a 5-item scale adapted from prior research (Li et al., 2021), covering listening, speaking, reading, writing, and vocabulary ($\alpha = 0.90$). HSK level was treated as a categorical variable for subgroup comparisons and as a continuous variable for regression analysis.

Academic Motivation Scale. A 12-item scale assessed intrinsic motivation (learning for the sake of learning) and extrinsic motivation (learning for external rewards or

requirements), adapted from the Academic Motivation Scale (Vallerand et al., 1992). The scale demonstrated acceptable reliability ($\alpha = 0.85$ for intrinsic, $\alpha = 0.82$ for extrinsic).

All instruments were translated to Chinese and back-translated to ensure conceptual equivalence (Brislin, 1970), and pilot-tested with 35 international students.

3.3.2 Qualitative Data Collection

Semi-structured interview guides were developed based on quantitative findings. Core questions included:

“How do you decide when to use AI tools and when not to use them in your Chinese learning?”

“Can you describe a situation where AI helped you learn, and a situation where you think AI prevented you from learning?”

“What factors do you think influence whether AI helps or harms your Chinese learning?”

“How do your teachers and the institution shape your approach to using AI?”

“What kind of guidance or support would help you use AI tools more effectively?”

Interviews were conducted in English or with an interpreter when necessary, each lasting 35–55 minutes. All interviews were audio-recorded with informed consent and transcribed verbatim.

3.4 Procedure

Ethical approval was obtained from the institutional review boards of all three participating institutions. Survey invitations were distributed via class advisors and WeChat groups during March–April 2026. Data collection occurred in two waves to maximize response rates. Interview participants were contacted via email or WeChat during May–June 2026, with interviews conducted in private campus offices or via video conferencing.

3.5 Data Analysis

Quantitative Analysis. Data were analyzed using SPSS 27.0 and Mplus 8.8. Descriptive statistics summarized AI usage patterns. Independent samples t-tests and one-way ANOVA examined group differences. Pearson correlations assessed relationships among variables. Hierarchical multiple regression identified significant predictors of empowerment and divide effects. Moderation analyses tested whether teacher guidance, AI literacy, and Chinese proficiency moderated the relationship between AI usage frequency and outcomes, using PROCESS macro for SPSS with 5,000 bootstrap samples.

Qualitative Analysis. Transcripts were analyzed using thematic analysis following Braun and Clarke’s (2006) six-phase approach. Coding was conducted using NVivo 14, with two independent coders achieving 87% inter-coder agreement.

Integration. The two data sets were integrated at the interpretation stage, with qualitative findings used to explain, elaborate, and contextualize quantitative results.

4. Quantitative Findings

4.1 AI Tool Usage Patterns

Descriptive statistics revealed extensive AI tool adoption. Of the 256 participants, 228 (89.1%) reported using at least one AI tool for Chinese learning purposes. Table 2 presents usage rates by tool category.

Table 2: AI Tool Usage Rates by Category

Tool Category	Ever Used (%)	Daily Use (%)	Weekly Use (%)	Mean Use Frequency (1–5)
Translation tools	94.5	52.7	34.0	3.94 (SD = 0.92)
Conversational AI	82.0	38.3	35.9	3.42 (SD = 1.04)
Intelligent writing assistants	67.2	23.4	34.4	3.01 (SD = 1.12)
Speech recognition/pronunciation	48.4	12.5	28.1	2.64 (SD = 1.21)
Personalized learning platforms	39.1	9.4	21.9	2.39 (SD = 1.18)
Other AI tools	25.8	5.5	14.8	2.08 (SD = 1.25)

Translation tools were nearly universal (94.5% ever-use, 52.7% daily use). Conversational AI (Deepseek, ChatGPT) was also widely used (82.0% ever-use, 38.3% daily use). The most frequently reported primary purposes were: vocabulary look-up (87.9%), understanding class materials (76.8%), completing homework assignments (71.3%), preparing written assignments (65.4%), and practicing reading comprehension (52.6%).

4.2 Determinants of AI Usage Frequency

Hierarchical regression identified significant predictors of AI usage frequency (Table 3). The final model explained 31.2% of variance. Prior technology experience was the strongest predictor ($\beta = 0.284$, $p < 0.001$), followed by Chinese proficiency ($\beta = -0.232$, $p < 0.001$)—lower proficiency students used AI more frequently—and intrinsic motivation ($\beta = -0.198$, $p = 0.002$)—students with higher intrinsic motivation used AI less frequently, suggesting they were more willing to struggle with language tasks independently.

Table 3: Hierarchical Regression Predicting AI Usage Frequency

Predictor	Model 1 β	Model 2 β	Model 3 β	VIF
Gender (female = 1)	0.082	0.074	0.068	1.18
Year of Study	-0.124*	-0.108	-0.096	1.22
HSK Level		-0.256***	-0.232***	1.35
Prior Technology Experience		0.312***	0.284***	1.41
Intrinsic Motivation			-0.198**	1.28
Extrinsic Motivation			0.124*	1.26
R^2	0.024	0.256	0.312	
ΔR^2		0.232***	0.056***	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

4.3 Empowerment and Divide Effects

The overall mean empowerment score was 3.72 (SD = 0.69), and the overall mean divide score was 2.89 (SD = 0.74). Learning efficiency received the highest empowerment rating (M = 3.95), while motivation and confidence received the

lowest ($M = 3.34$). Technological dependency was the most prominent divide dimension ($M = 3.21$), with over half of participants (54.3%) scoring above the midpoint.

4.4 Differential Impacts by Student Characteristics

By HSK Level. Significant differences were observed across HSK levels for both empowerment and divide effects. For empowerment, $F(3, 252) = 6.78$, $p < 0.001$, with HSK Level 5+ students reporting the highest empowerment ($M = 4.01$, $SD = 0.61$) and those below Level 3 reporting the lowest ($M = 3.38$, $SD = 0.72$). For divide effects, HSK Level 5+ students reported significantly lower divide scores ($M = 2.52$, $SD = 0.68$) compared to students below Level 3 ($M = 3.24$, $SD = 0.75$), $F(3, 252) = 7.45$, $p < 0.001$. This pattern suggests that higher language proficiency is associated with both greater benefit and lower risk from AI tool use.

By Digital Literacy. Students with above-median AI literacy reported higher empowerment ($M = 3.98$, $SD = 0.58$ versus $M = 3.42$, $SD = 0.72$, $t(254) = 6.78$, $p < 0.001$) and lower divide effects ($M = 2.52$, $SD = 0.65$ versus $M = 3.28$, $SD = 0.72$, $t(254) = -8.94$, $p < 0.001$). This gap was particularly pronounced for critical thinking erosion ($M = 2.38$ versus $M = 3.24$, $t(254) = -7.82$, $p < 0.001$).

By Academic Motivation. Students with high intrinsic motivation reported higher empowerment ($M = 3.92$, $SD = 0.62$ versus $M = 3.48$, $SD = 0.74$, $t(254) = 5.12$, $p < 0.001$) and lower divide effects ($M = 2.67$, $SD = 0.68$ versus $M = 3.14$, $SD = 0.76$, $t(254) = -5.24$, $p < 0.001$) compared to high extrinsic motivation students.

4.5 Predictors of Empowerment and Divide Effects

Hierarchical regression identified significant predictors of empowerment and divide effects (Tables 4 and 5).

Table 4: Hierarchical Regression Predicting Empowerment Effects

Predictor	Model 1 β	Model 2 β	Model 3 β	Model 4 β	VIF
Gender (female = 1)	-0.042	-0.038	-0.031	-0.028	1.18
Year of Study	-0.156**	-0.124*	-0.098	-0.087	1.22
HSK Level		0.234***	0.168**	0.141*	1.38
AI Literacy		0.342***	0.281***	0.215***	1.52
Teacher Guidance			0.287***	0.248***	1.44
Intrinsic Motivation				0.194**	1.47
R^2	0.028	0.267	0.342	0.378	
ΔR^2		0.239***	0.075***	0.036**	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 5: Hierarchical Regression Predicting Divide Effects

Predictor	Model 1 β	Model 2 β	Model 3 β	Model 4 β	VIF
Gender (female = 1)	0.067	0.072	0.058	0.052	1.18
Year of Study	0.182**	0.152*	0.118*	0.104	1.22
HSK Level		-0.298***	-0.244***	-0.218***	1.38
AI Literacy		-0.318***	-0.262***	-0.204**	1.52
Teacher Guidance			-0.267***	-0.231***	1.44
Intrinsic Motivation				-0.148*	1.47
R^2	0.037	0.282	0.361	0.382	
ΔR^2		0.245***	0.079***	0.021*	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

AI literacy was the strongest predictor of empowerment ($\beta = 0.215$, $p < 0.001$), followed by teacher guidance ($\beta = 0.248$, p

< 0.001). HSK level emerged as the strongest protective factor against divide effects ($\beta = -0.218$, $p < 0.001$), followed by teacher guidance ($\beta = -0.231$, $p < 0.001$).

4.6 Moderation Analyses

Teacher Guidance as Moderator. Teacher guidance significantly moderated the relationship between AI usage frequency and divide effects (interaction $\beta = -0.162$, $p = 0.004$). Among students with low teacher guidance, increased usage frequency was associated with substantially higher divide effects ($\beta = 0.38$, $p < 0.001$). Among students with high teacher guidance, this relationship was attenuated ($\beta = 0.12$, $p = 0.087$).

HSK Level as Moderator. HSK level moderated the relationship between AI usage frequency and divide effects (interaction $\beta = -0.154$, $p = 0.008$). For students below HSK Level 3, frequent AI use was associated with significantly higher divide effects ($\beta = 0.42$, $p < 0.001$). For HSK Level 5+ students, this relationship was non-significant ($\beta = 0.08$, $p = 0.312$).

AI Literacy as Moderator. AI literacy moderated the relationship between usage frequency and empowerment (interaction $\beta = 0.148$, $p = 0.012$). The positive effect of usage frequency on empowerment was stronger among students with higher AI literacy.

5. Qualitative Findings

Five overarching themes emerged from thematic analysis, each providing explanatory depth to quantitative patterns.

5.1 Theme 1: The Proficiency-Dependency Paradox

Participants consistently articulated a paradox: those who most needed AI assistance were most vulnerable to its negative effects. This theme directly explains why HSK level emerged as the strongest protective factor against divide effects.

A first-year student from Bangladesh illustrated this paradox: “When my Chinese was very poor, I used translation for everything. I copied and pasted. I didn’t learn. But my friend whose Chinese is good, she uses AI as a tool. She checks her own work. I think AI helps her more than me, even though I use it more” (P12, Male, Year 1, Navigation).

A third-year student from Indonesia reflected: “In first year, I used AI constantly. I passed my courses but learned very little Chinese. Now in third year, I can do more myself. I use AI only for things I cannot do. This is better. The problem is: when you most need to learn, you most need the tool, but the tool stops you from learning” (P03, Female, Year 3, International Trade).

5.2 Theme 2: The Role of Teacher Guidance

Participants who received clear teacher guidance reported more balanced usage patterns. A student from Thailand described a positive experience: “My teacher showed us how to use AI to check our writing after we wrote, not to write for

us. She said: ‘AI is like a calculator—it helps with calculations, but you still need to know math.’ This helped me understand when to use AI” (P08, Female, Year 2, International Trade).

Conversely, students who received no guidance reported problematic use. A participant from Nigeria stated: “None of my teachers talk about AI. I don’t know if it is allowed or not. I just do what I think is okay. Sometimes I feel I am doing something wrong, but nobody tells me” (P11, Male, Year 2, Marine Engineering).

5.3 Theme 3: The Performance Paradox

Participants articulated awareness of the performance paradox—short-term gains versus long-term erosion. A student from Uzbekistan noted: “AI helps me get good grades. My written assignments are good. But I know if I have to write an email to a Chinese company, I cannot do it. AI does the work, but I don’t learn. I am worried about my future career” (P06, Male, Year 1, Navigation).

A student from Kenya reflected on this tension: “It is like going to the gym and having someone else lift the weights for you. You look like you exercised, but your muscles don’t grow. I passed HSK Level 4, but I used AI so much that I cannot speak real Chinese” (P09, Female, Year 2, Hospitality).

5.4 Theme 4: Motivational Differences

Motivational differences substantially shaped AI use patterns. Intrinsically motivated students reported strategic, learning-oriented use. A student from Vietnam explained: “I love learning Chinese. When I use AI, I always try to learn from it. I read the translation and then try to understand why it is translated that way. This helps me learn new patterns” (P05, Female, Year 1, International Trade).

Extrinsically motivated students reported more instrumental use. A student from Pakistan stated: “I need to pass the HSK exam to graduate. I use AI to prepare for the exam, to do practice questions. I don’t care if I learn or not. I just need the certificate” (P07, Male, Year 2, Marine Engineering).

5.5 Theme 5: Articulated Support Needs

Participants identified several forms of support they desired regarding AI use. These clustered into four categories:

First, explicit guidelines. “I just want to know clearly: can I use AI for homework? Can I use it for exam preparation? What is okay and what is not okay?” (P05, Female, Year 1).

Second, AI literacy training. “I want a workshop about how to use AI effectively—how to write good prompts, how to check if AI gives correct information, how to use AI to help my learning without becoming dependent” (P08, Female, Year 2).

Third, teacher modeling. “If teachers show us how they use AI, and explain their thinking, this would help us learn. It should be part of the class” (P06, Male, Year 1).

Fourth, balanced assessment. “Exams should test our real

ability, not our ability to use AI. But teachers should design tasks where AI use is part of the task, and we still need to show understanding” (P14, Male, Year 3, Navigation).

6. Discussion

6.1 Synthesis of Findings

This study investigated the determinants and differential impacts of AI tool usage in Chinese language learning among international students in Jiangsu vocational colleges. The findings reveal a complex picture of widespread adoption, significant intra-group variation, and critical moderating factors that determine whether AI use empowers or divides.

Intra-Group Variation. The most striking finding is the significant intra-group variation in AI use patterns and outcomes. While nearly 90% of students use AI tools, the nature and consequences of this use vary dramatically. This variation challenges the temptation to treat “international students” or “AI users” as homogeneous groups. Instead, we must recognize that AI use is a heterogeneous phenomenon shaped by individual and contextual factors.

The Proficiency-Dependency Paradox. The finding that lower-proficiency students are most vulnerable to negative AI effects represents a particularly concerning pattern. The students who most need support are most at risk of AI-induced learning compromise. This constitutes a new form of educational inequality—what we term the “AI competence divide” or “AI literacy divide”—that compounds existing linguistic disparities.

The Critical Role of Teacher Guidance. Teacher guidance emerged as a consistently significant protective factor against divide effects and a promoter of empowerment. This finding has important practical implications: institutional investment in teacher professional development regarding AI integration is not merely beneficial but essential.

The Performance Paradox. The documented awareness among students of the performance paradox—short-term gains versus long-term erosion—is both encouraging and concerning. Encouraging because students are not naive about AI’s risks; concerning because awareness alone does not prevent problematic use. Institutional support is needed to translate awareness into effective practice.

6.2 Theoretical Contributions

First, this study extends van Dijk’s (2024) digital divide framework by identifying the “AI literacy divide” as a distinct and consequential form of digital inequality. Students may have equal physical access to AI tools yet differ dramatically in their capacity to use them effectively and critically. We propose that van Dijk’s framework be extended to include AI literacy as a distinct dimension of skills access.

Second, the findings contribute to understanding the conditions under which technology enhances versus hinders learning. The “empowerment-divide dualism” we observed, with significant moderating relationships, supports a socio-technical perspective in which outcomes are

co-produced by technology, user characteristics, and social context (Warschauer, 2011).

Third, the study provides empirical grounding for conceptualizing AI literacy in language learning contexts. Our findings suggest that AI literacy for language learning includes both general AI competencies and language-learning-specific competencies, such as understanding the relationship between AI assistance and communicative competence development.

6.3 Practical Implications

Differentiated Support Based on Proficiency. Given that lower-proficiency students are most vulnerable to negative AI effects, institutions should provide targeted support to this group. This could include closer monitoring of AI use in lower-level language courses, explicit instruction on appropriate AI use, and assessments that reduce the incentive for unreflective AI use.

Teacher Professional Development. The significant role of teacher guidance suggests that institutions should invest in teacher professional development regarding AI integration. Teachers need support in understanding AI tools, developing AI-aware pedagogical strategies, communicating clear expectations, and designing appropriate assessments.

AI Literacy Integration. AI literacy training should be integrated into the curriculum, covering understanding AI capabilities and limitations, critical evaluation of AI output, effective prompt formulation, and ethical AI use.

Clear Institutional Policies. Institutions should develop clear, accessible policies specifying acceptable AI use in different contexts, developed with student input and reviewed regularly as technology evolves.

Assessment Reform. Traditional assessments may no longer validly measure student competence. Institutions should consider in-class supervised assessments, assessments that explicitly incorporate AI use, process-oriented assessments, and oral assessments testing authentic communicative competence.

6.4 Limitations and Future Directions

Cross-Sectional Design. The cross-sectional nature precludes causal inferences. Future research should employ longitudinal designs to track how usage patterns and effects evolve over time.

Sampling Limitations. Data were collected from three Jiangsu institutions, limiting generalizability. Future research should employ multi-site designs across different provinces and institution types.

Self-Report Measures. Reliance on self-reported data may introduce biases. Future research should incorporate behavioral data, observational data, and performance data to triangulate findings.

Limited Attention to Tool-Specific Effects. This study

examined AI tool usage broadly. Future research should examine whether different tool categories have systematically different effects.

7. Conclusion

This study examined the determinants and differential impacts of AI tool usage in Chinese language learning among international students in three Jiangsu vocational colleges. Nearly 90% of participants used AI tools, with translation tools being most common. Significant intra-group variation was observed: higher proficiency students derived greater benefit and experienced fewer negative effects, while lower-proficiency students were most vulnerable to AI-induced learning compromise. AI literacy and teacher guidance emerged as critical protective factors. The findings extend digital divide theorizing to AI-enhanced language learning contexts and provide practical guidance for vocational institutions seeking to help international students use AI responsibly and effectively. As AI technology continues to advance, developing students' AI literacy and creating supportive institutional environments will be essential for ensuring that AI empowers rather than divides.

Acknowledgments

This research is a phased achievement of the Jiangsu Provincial College Students' Innovation and Entrepreneurship Training Program "AI Empowerment and Digital Divide: Research on the Current Status and Impact of AI Tool Usage in Chinese Language Learning among International Students" (Project Number: GX-2025-010). We extend our gratitude to the project team members and all participating students for their support and contributions.

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